Credit Default Swaps as Indicators of Bank Financial Distress

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Abstract

We examine whether CDS contracts written on individual banks are effective leading indicators of bank financial distress during a period of systemic bank crisis. Changes in CDS spreads are found to yield a robust signal of failure across a set of European and US banks, in keeping with indirect market discipline. Furthermore, changes in CDS spreads provide information about the condition of banks which supplements that available from equity markets and contained in accounting metrics. Our findings hold out-of-sample, for various cohorts, for subordinated CDS spreads, for idiosyncratic changes in CDS and are robust to the use of alternative measures of bank distress, including rating downgrades and accounting risk.

Keywords: Bank Failure, Market Discipline, Credit Default Swap, CDS

1. Introduction

In contrast to many other industries, banks, and financial institutions more generally, are subject to high levels of regulatory oversight. Regulatory supervision may also be supplemented by market forces in two primary ways (Flannery, 2001). First, changes in market prices may be linked to increased funding costs, limiting risk taking and inducing direct market discipline. Second, market prices may act as a signal to investors, policy makers and supervisors regarding the condition of individual financial institutions, leading to indirect market discipline. Moreover, such market signals may be employed as inputs to early warning models of bank financial distress. Previous

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studies have indicated mixed success in using market-based information to distinguish between safe and distressed banks, in particular for bond markets. Firm-level credit default swaps (CDS) present many advantages over bond markets in terms of price discovery, liquidity and standardization. In light of these benefits, we address the following research question: Do firm-level CDS contracts act as effective and distinct leading indicators of bank vulnerability to distress?

For banks with actively traded securities, changes in prices of equity and debt act as a source of market information regarding the market's perception of their financial condition. Equity investors appear well placed to provide market discipline, given their status as residual claimants in the event of default. One argument against this view is that equity investors may condone increased risk taking, being the primary beneficiaries from any upside gains (Gropp *et al.*, 2006). For this reason, bond markets and, in particular, subordinated debt have been considered as a means to promote market discipline. If debt markets accurately reflect bank risks, banks may be discouraged from adopting riskier strategies to ward off potential increases in funding costs. In practice, however, the use of debt markets to monitor banks is beset by implementation problems, such as differing yields for bond issues from a single institution, and illiquidity (Gropp *et al.*, 2006; Chen *et al.*, 2007).

We examine whether single-name CDS can distinguish between safe and distressed banks using a sample encompassing the global financial crisis. A CDS is a protection or insurance agreement between two parties, whereby the protection seller undertakes, in exchange for a premium paid by the protection buyer, to make a payment if a specified credit event occurs (Chiaramonte and Casu, 2013). As a signal of bank condition, CDS offer a number of differences and potential benefits relative to corporate debt markets. First, the CDS market is attractive due to smaller trading frictions compared to the underlying bond (Oehmke and Zawadowski, 2014). Second, CDS market prices are standardized with constant maturity, whereas uniform bond yields can only be obtained by interpolating bond yields of different maturities (Blanco *et al.*, 2005). Third, CDS markets are more liquid than corporate debt markets (Longstaff *et al.*, 2005). Finally, CDS spreads tend to lead bond markets in price discovery (Blanco *et al.*, 2005). Related to this, CDS markets are also shown to reveal information in advance of the equity market (Acharya and Johnson, 2007). Given these strong relative benefits, CDS contracts seem well placed to act as an indicator of bank distress, thus providing indirect market discipline.

In this paper we provide the first analysis of the capacity of CDS contracts on individual banks to act as a signal of a bank's financial condition. Relative to accounting and equity information, we investigate the marginal contribution of changes in CDS spreads in forecasting bank distress during the years 2004-2012, a period of systemic banking crisis during which many banks failed. Previous literature has considered the propensity of aggregate CDS spreads (based on broad CDS indices) to act as a signal of bank distress (Knaup and Wagner, 2012), investigated the drivers of bank CDS spreads during the global financial crisis (Chiaramonte and Casu, 2013) and the interdependence of sovereign and bank CDS during times of market turbulence (Alter and Schüler, 2012). In contrast, this paper focuses on single-name CDS contracts associated with debt of individual institutions.[1]

Empirical findings indicate that changes in CDS spreads help to explain forthcoming distress in banks, whilst controlling for alternative drivers. The economic significance is substantial: a one standard deviation increase in CDS spread changes is associated with an increase in bank failure probability ranging from 7% to 14%. Moreover, our results indicate that CDS spreads incorporate information about the condition of banks which is above and beyond that available from both equity market indicators and traditional accounting metrics. This is in keeping with indirect market discipline, as CDS contracts signal increasing borrowing costs for distressed firms. Findings are shown to be robust for alternative dependent variables (rating downgrades and accounting risk), subordinated CDS, excluding US banks, for various cohorts, and for excess and idiosyncratic changes in CDS. While our findings are constrained by a small data sample of banks having traded CDS, the evidence presented points to the potential for CDS to contribute to indirect market discipline.

In the following section we describe literature relevant to this study. Data and methodology are detailed in Section 3. Empirical results are provided in Section 4. Section 5 concludes.

2. Related Literature

Corporate governance of financial institutions is constrained by many factors, not least the problem that small depositors may not be able to distinguish between safe and risky institutions, the

[1] Single-name or firm-level CDS contracts are a derivative where the underlying instrument is a bond of a particular company.

opaque nature of banking assets, and the dangers of contagion from a single distressed institution (Flannery, 1998). Thus, government oversight aims to promote stability in the banking sector, protecting depositors through provision of deposit insurance and acting as a lender of last resort to mitigate contagion due to illiquidity. Market discipline, as provided for in the Basel II accord, aspires to complement regulatory oversight. This may be achieved through two channels: by means of direct influence on management risk taking and, indirectly, through market monitoring of banks' financial position (Flannery, 2001). If market discipline exists, then changes in the prices of liabilities or equities, both absolute and relative to competitors, should be related to changes in measures of risk (Mayes, 2004; Gorton and Santomero, 1990). On this basis, empirical evidence for market discipline has been mixed. Flannery (1998) suggests that investors could provide further market discipline for large, traded U.S. banks, but that this may be impeded by government oversight and the potential for state intervention in distressed institutions.

The failure and near-failure of many systemically important banks during the global financial crisis and subsequent European sovereign debt crisis, has again brought banking regulation to the forefront. The considerable underperformance of many banks during this period has been variously attributed to a dependence on short-term funding, high leverage, lack of diversification, credit expansion and higher share of volatile non-interest income (Demirguc-Kunt *et al.*, 2013; Beltratti and Stulz, 2012; Altunbas *et al.*, 2011). Moreover, factors common to previous crises, including historical bank equity performance, have been shown to explain distress for individual institutions during the global financial crisis (Cole and White, 2012; Fahlenbrach *et al.*, 2012). In this study, we build on previous analyses of bank failure during the global financial crisis. The abundance of distressed banks during the period encompassing the global financial crisis and the introduction of novel financial instruments such as CDS provide a fresh opportunity to determine whether financial markets are helpful in explaining the failure of financial institutions.

Evidence suggests that equity markets display efficiency in processing information and, so, should act as a strong indicator of a firm's financial position (Gropp *et al.*, 2006). Considering the potential of equity markets to act as a signal of bank fragility, Distinguin *et al.* (2006) and Curry *et al.* (2008) provide evidence of forecasting ability. In contrast, Krainer (2004) finds little additional ability to forecast changes in supervisor ratings from equity market information relative to supervisory factors. Gropp *et al.* (2006) use equity market data to develop a distance-to-default (*DD*) metric, suggested as a complement to bond information in signaling bank fragility. Milne (2014) find poor forecasting performance of the DD measure prior to the onset of the subprime crisis. Bliss and Flannery (2002) find limited evidence for equity market discipline in influencing managerial actions. In this study, we again assess whether equity markets help in distinguishing between safe and distressed banks and provide a comparison to the contribution of CDS markets.

Changes in bond credit spreads provide a further source of information regarding a bank's financial condition. Evidence for the effectiveness of debt markets is, however, mixed. Krishnan *et al.* (2005) show that credit spread levels are associated with risk taking behavior but that changes in spread levels are not. Gorton and Santomero (1990) find little support for subordinated debt in limiting bank risk taking following the 1980s expansion of the government safety net. Similarly, Evanoff and Wall (2001) suggest that market information embedded in subordinated debt yield spreads is too noisy to serve as a trigger for corrective action. Considering the recent global financial crisis, Miller *et al.* (2015) find no evidence that subordinated note yields act as a reliable signal of bank distress. In sharp contrast, a variety of studies have documented evidence that debt markets reflect the riskiness of financial institutions (see, for example, Gropp *et al.*, 2006; Sironi, 2003). Models examining the potential of subordinated debt to provide market discipline have also arrived at disparate conclusions (Chen and Hasan, 2011; Niu, 2008; Blum, 2002).

Credit default swaps have been actively traded since the early 2000s, with liquidity and availability generally increasing over the decade.[2] CDS have a variety of features which may make them a better proxy than bonds in providing market discipline for banks. Oehmke and Zawadowski (2014) suggest that speculative credit trading volume concentrates in the CDS rather than bond markets. Moreover, CDS spreads are less affected by illiquidity than bond spreads: Longstaff et al. (2005) find that the nondefault component of corporate bonds is strongly related to bond-specific illiquidity measures as well as aggregate bond market liquidity measures. Huang and

[2]CDS notionals doubled each year from 2004 ($6.4 trillion) until 2007 ($58.2 trillion) before being hit by the outbreak of the financial crisis in 2008 (where notionals traded declined to $42 trillion). By the end of 2012, the size of the CDS market was similar to the period preceding the subprime crisis of 2007. See www.bis.org and www.dtcc.com for more information on notional amounts traded on both single-name and index CDS contracts.

Huang (2012) and Elton *et al.* (2001) also find that credit risk typically accounts for less than 20 percent of corporate-Treasury yield spreads. Blanco *et al.* (2005) documents a higher price discovery for CDS spreads relative to corporate bonds. Finally, evidence of faster CDS information processing ability relative to the equity market is also shown (Acharya and Johnson, 2007). The authors find that CDS markets reveal information in advance of the equity market for entities that experience (or are likely to experience) adverse credit events.

Interest in bank CDS has increased markedly since the global financial crisis. Stânga (2014) and Avino and Cotter (2014) examine the relationship between bank and sovereign CDS spreads from the onset of the global financial crisis. Analyzing the potential for market discipline in the CDS market, Völz and Wedow (2011) point to the influence of bank size on CDS prices. Chiaramonte and Casu (2013) evaluate the determinants of bank CDS spreads and demonstrate a tendency for considerable time variation. Hasan *et al.* (2016) also find a significant contemporaneous relationship between CDS spreads and structural variables, and a weaker link with CAMELS indicators. Considering the case of a single distressed bank, Northern Rock, Hamalainen *et al.* (2012) determine that equity markets provide a stronger signal of impending problems than debt or CDS markets. Finally, a number of studies have used aggregate CDS spreads and CDS indices to examine bank fragility (Ballester *et al.*, 2016; Knaup and Wagner, 2012; Calice *et al.*, 2012). Building on the extant literature considering banks and CDS contracts, the present study assesses the cross-sectional ability of single-name bank CDS contracts to perform a disciplining role on banks.

3. Data and Methodology

We now describe our sample of bank CDS, in addition to the accounting-based and market-related variables employed as inputs to the bank distress models. Theory and mathematical representation of the logit model used to explain bank failure is further detailed.

3.1. Data

In order to test the ability of CDS to distinguish between safe and distressed banks, we obtain single-name five year CDS spreads from Markit. Markit provides consensus CDS prices after aggregating contributions from various dealers on a daily basis. The initial data set contains 538 financial firms with senior CDS data. We restrict our main focus to banks and start by applying data filters, including "Banks", "Diversified Banks" and "Financial Services" sectors, leaving 259 firms. Banks whose headquarters are not in the US or Europe are then removed, resulting in 142 firms. Next, excluding firm without accounting information results in a final sample of 60 firms with CDS data available over the sample period 2004-2012. The size of the final sample, while potentially smaller than might be available for an analogous study considering equities, is larger than available for previous studies considering cross-sectional properties of bank CDS, such as Ballester *et al.* (2016), Yang and Zhou (2013), Annaert *et al.* (2013) and Eichengreen *et al.* (2012).

We select the 2004-2012 period because (i) we are interested in assessing the explanatory power of CDS before and around periods of crisis (in particular, the financial crisis of 2007-2009 and the subsequent European sovereign debt crisis beginning from 2010); (ii) the CDS market is well developed and mature during this cohort. These choices help to ensure that our empirical study is focused on a liquid, actively traded security during a period of significant instability for the banking industry. Furthermore, we focus primarily on annual data as fundamental accounting data is not available on a more regular basis, especially for European banks. The set of cross-sectional bank CDS spreads are then used to investigate whether single-name CDS help in explaining bank financial distress. We use the yearly change in the log CDS spread (ΔCDS) as the main variable to explain bank default. The control variables employed to control for various facets of banking risk consist of both accounting and market variables. Accounting variables employed are obtained from Bureau Van Dijk's BankScope database and include the tier 1 regulatory capital ratio (*T1RC*), the loan-loss-provisions-to-assets ratio (*LLPTA*), the cost-income ratio (*CI*), the return on average equity (*ROAE*), the liquidity ratio (*LADEPST*) and the log of total assets (*SIZE*).

In this paper, the marginal ability of CDS spreads to explain bank failure relative to equity-derived measures is further studied. Individual equity prices are obtained from Thomson Datastream. Market related variables are represented by the log stock return, calculated on an annual basis (*STOCK*) and the distance-to-default measure (*DD*) computed for each time period t using equity market volatility as in Gropp *et al.* (2006).

We next define our main measure of bank distress employed. During the global financial crisis and subsequent sovereign debt crisis, a large number of European and US banks suffered financial distress of one form or another. A bank is defined as having failed if it was nationalized or recapitalized, using either ordinary or preferred share capital, by the state. Data regarding the failure status of each bank was gathered from a variety of sources (Conlon and Cotter, 2014; Altunbas *et al.*, 2011; Goddard *et al.*, 2009; Petrovic and Tutsch, 2009). Our measure is binary, taking a value of one when a bank failed, and a value of zero otherwise. In Appendix A we present the full list of variables used in our study.

Panel A of Table 1 provides a summary of the main properties of our primary failure indicator during the period 2005-2012. A large proportion of the failures occur in 2008 with the outbreak of the subprime crisis: 20 banks from a total of 60 failed and the failure rate is highest at 33.3%. During the sample period, a total of 31 banks are deemed to have been either nationalized or recapitalized and regarded as having failed. From a total of 60 banks, we have 11 US institutions which failed by the end of 2009. While the US was the epicenter of the global financial crisis, the number of failed large banks was small relative to Europe. The analysis of 11 failed US institutions is in keeping with Beck *et al.* (2013), where the sample consisted of 12 failed US and 43 failed European banks. Furthermore, Ballester *et al.* (2016) document only 5 US banks with available CDS, compared to 50 European banks over a similar time period.

In Table 1 we also show the summary statistics for all the explanatory variables used in the empirical analysis for both the whole sample of banks (Panel B) and the sample of failed banks (Panel C) during the period 2005-2011.[3] The mean and standard deviation of the change in log CDS spreads is higher for the sample of failed banks than for the entire sample. Similar differences can be observed for most of the remaining variables. Failed banks have less capital, higher cost to income ratio, a higher return on average assets and are larger than the average. In our sample 17 banks are unlisted and, for this reason, the number of observations for the stock market variables (namely, *STOCK* and *DD*) are reduced relative to the other variables.

[3]Note that we exclude year 2012 from this table because our sample period ends in 2012. Thus, for banks which failed in 2012, we would be using explanatory variables up until year 2011.

3.2. Methodology

In order to investigate the explanatory power of CDS spreads for banking failure, we follow Shumway (2001) and Chava and Jarrow (2004) and estimate the probabilities of failure over the next period using a logit model. In particular, we assume that the marginal probability of failure over the next period follows a logistic distribution and is given by:

$$P_{i,t}\left(Y_{i,t+1} = 1\right) = \frac{1}{1 + e^{-\alpha-\beta X_{i,t}}} \tag{1}$$

where $P_{i,t}$ is the probability at time t that bank i will fail in the next time period. $Y_{i,t+1}$ is a dummy variable taking on the value of 1 (0) if the bank failed (did not fail) in period $t + 1$. $X_{i,t}$ is the vector of n explanatory variables known at the end of period t. α and β represent the constant and slope parameters characterizing the logistic function, respectively and are estimated via maximum likelihood. A higher value of $\alpha + \beta X_{i,t}$ indicates a higher probability of failure.

Common to most studies incorporating both market and accounting variables in explaining failure, we face the issue that they are not available at the same frequencies. Following Arena (2008) and Distinguin *et al.* (2006), we use accounting-based information measured yearly on December 31st of each year. Similarly, market-based information related to CDS and equity are also measured on a yearly basis on the final trading day of each year.[4]

The coefficients from a logistic function based model based can be used to quantify the marginal effect of a change in any of the explanatory variables, X, on the probability of failure, P, using:

$$\frac{\partial P}{\partial X} = \frac{dP}{d(\alpha+\beta X)} \times \frac{\partial(\alpha+\beta X)}{\partial X} = \frac{e^{-\alpha-\beta X}}{\left(1 + e^{-\alpha-\beta X}\right)^2} \times \beta. \tag{2}$$

The marginal effect is not constant because it depends on the specific values taken on by the explanatory variables X. A common procedure, adopted in this study, is to evaluate the marginal effect for the sample means of the explanatory variables.

[4]The majority of banks in our sample do not report interim results with sufficient granularity, so, in this study, we use annual accounting data to forecast failure over the following year.

4. Empirical Results

This section presents our main empirical results. The initial analysis considers the univariate explanatory power of CDS spread changes. We then assess whether this explanatory power is affected by introducing various accounting and market variables. We finally show how including CDS changes in logit models increases the out-of-sample predictions of the models.

4.1. CDS spread changes and bank failure

We first empirically establish whether variations in single-name CDS spreads can be used as early warning signals of bank financial distress. In particular, we want to examine whether the use of CDS spread changes can improve the performance of bank failure models over and above models that only use accounting and/or stock market indicators.

We start our empirical analysis by estimating a logit model with CDS spread changes as our only explanatory variable. The results in Table 2 demonstrate a highly significant positive coefficient of 1.59.[5] Having ascertained that CDS spread changes significantly explain bank failure, we next control for various facets of banking risk. To this end, accounting variables, stock returns and the DD measure, are incrementally incorporated in the model as shown in Table 2. Coefficient estimates for the CDS spread change remain positive and highly significant (at the 1% level) in all specifications. The tier 1 regulatory capital ratio is also highly significant and negative. The DD measure is significant at the 5% level and is negative. Stock returns are insignificant once we control for other aspects of banking risk. While previous research has found mixed explanatory power associated with bank bond yields, these findings suggest that CDS spreads have strong ability to discriminate between safe and distressed banks, even relative to equity market indicators.[6]

[5]In addition to yearly log changes, we also consider log changes in CDS spreads for 3, 6 and 9 months before the forecasting interval. The results, Table A.1 of the Online Appendix, demonstrate a highly significant positive coefficient for all horizons. For these univariate regressions the highest value of the McFadden R-squared is obtained for the 1-year log change in CDS spread. In model M5, we also report the logit estimation when 1-year log stock returns are instead used as the only explanatory variable. The estimated coefficient is negative but not statistically significant. To explore the marginal explanatory ability of CDS spread changes relative to stock returns, the last model specification (M6) includes both log CDS spread changes and log stock return as explanatory variables. Estimated coefficients have the expected sign and are significant at the 10% significance level providing initial evidence for marginal explanatory power of CDS relative to equity returns. This complementary explanatory power suggests that CDS markets impound additional information over and above equity markets, relevant to policy makers and regulators.

[6]In Table A.3 of the Online Appendix we examine whether the explanatory power of CDS spread changes varies

In order to get an idea of the relative influence of these variables, the marginal impact on failure probability from a one-standard-deviation increase in each explanatory variable is examined using Equation 2, assuming an initial mean value of the explanatory variables. For instance, if we consider the sixth specification in Table 2 (M6), a one-standard-deviation increase in the CDS spread change would increase the probability of failure by 14% of its initial value. Similarly, if we focus on the seventh specification (M7), a one-standard-deviation increase in the CDS spread change determines an increase in the failure probability of 12% of its initial value.[7]

4.2. Testing for the predictive ability of failure models

In this subsection, we conduct tests of out-of-sample predictive ability of several logit models of forthcoming bank failure. Clustering of bank failures in our sample in year 2008 (20 out of 31 failed banks emanate from 2008), leads us to focus on the 2005-2008 period and estimate model parameters with a starting estimation sample which uses 2005-2007 observations. The estimated coefficients are then employed to compute the ex-ante bank default probabilities for year 2008.

Various studies have investigated the out-of-sample performance of bankruptcy prediction models (Bauer and Agarwal, 2014; Betz *et al.*, 2014; Agarwal and Taffler, 2008). In a similar vein, we employ a Receiver Operating Characteristics (ROC) curve to analyze out-of-sample performance.[8]

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with a bank's business model and find stronger results for investment banks. In untabulated results, we also examine the explanatory power of CDS spread levels and the volatility of CDS spread changes. While both are significant in isolation, they become insignificant when a full model specification is used which includes the DD measure. Furthermore, we consider the role of country-level characteristics on the forecasting ability of CDS changes for bank failure. We find that CDS spread changes remain highly significant indicators of bank distress after controlling for these macroeconomic covariates. We also employ an alternative Cox proportional hazard estimation approach and find that changes in CDS spreads are highly significant when adding the additional control variables. We finally exclude US banks from our sample and run the same logit regressions as in Table 2, obtaining very similar results. Full results for these additional tests are available from the authors on request.

[7] In the Online Appendix, we provide numerous tests to validate the robustness of our findings. First, we evaluate the explanatory power of CDS spread changes during the shorter period 2005 – 2008 as the majority of bank failures in our sample occurred in 2008 (see Table A.2). Second, we use alternative measures for CDS spread changes that neutralize the effect of general market conditions (see Table A.4). Third, we employ alternative dependent variables: a binary downgrade indicator and two additional continuous variables, namely ROAA volatility and the Z-score (see Table A.5). Finally, we test whether subordinated CDS spread changes have similar explanatory power for bank distress during our sample period (in Table A.6). In all cases, we find that changes in CDS spreads are strongly associated with bank failure.

[8] The receiver operating characteristic measures the trade-off between correctly predicted failure and incorrectly predicted non-failures. An ROC area under the curve of 1 would indicate complete forecasting accuracy. An ROC less than 0.50 suggests that random selection would better predict failure out-of-sample than the prediction model.

To determine the ability of CDS changes to distinguish between failed and surviving banks out-of-sample, we adopt a simulation approach. In addition to testing our approach on data unused in determining model parameters, this has the added benefits of facilitating analysis of the importance of sample size on results. For each logit model, we run 1000 simulations of the ROC curve area. For each simulation, model parameters are estimated during the 2005-2007 period using 50 banks randomly selected. The estimated model coefficients are then used to predict default probabilities for the remaining 10 banks which were not used in building the model.[9]

Results are detailed in Table 3. We have four simple models, each considering a single representation of banking risk (based on ΔCDS, *STOCK*, *Accounting* and *DD*). The *Accounting* model only uses accounting variables (namely, *T1RC*, *LLPTA*, *CI*, *ROAE*, *LADEPST*, *SIZE*) as covariates to predict failure. We then run five bivariate models that combine the variables used in the univariate models. Finally, we run two trivariate models, incorporating three sets of risk predictors.

The area under the ROC curve (AUC) is computed using the trapezoidal rule and its simulated mean value reported in column 2 of Table 3 for each model. Column 3 shows the simulated mean AUC standard error based on the unbiased estimator of Hanley and McNeil (1982), column 4 the test statistic for the null hypothesis that the AUC is equal to 0.5 and column 5 the simulated mean accuracy ratio (AR = 2 * (AUC - 0.5)) based on Engelmann *et al.* (2003). Column 6 reports the *t*-statistic of a two-sample one-tailed *t*-test for the null of equality between the simulated mean AUC of a univariate logit based on ΔCDS and that obtained from any of the remaining ten logit models. When considered alone, ΔCDS has an AUC of 0.64, significantly different from the accuracy obtained from random sampling. Combining ΔCDS with accounting or stock returns results in a decrease in AUC, in keeping with the finding that information from the stock market or accounting information adds little additional information relative to CDS. Combining ΔCDS with DD, we get a AUC of 0.70, greater than that from ΔCDS alone. This predictive analysis further confirms that CDS market information can be employed to generate useful predictive signals of bank distress.

[9] As a test of robustness, we also estimate the models using randomly chosen 30 banks to generate default probabilities for the remaining 30 banks and obtain analogous results.

5. Conclusions

This study is among the first to examine whether single-name CDS contracts help explain bank failure, in keeping with the premise of indirect market discipline. For a sample of 60 banks, we examine whether increases in CDS spread changes are associated with greater probability of failure. Furthermore, we control for an extensive range of alternative market and accounting measures. The primary finding of the paper is that relative changes in firm-level CDS spreads are strongly and significantly associated with future bank failure. This result holds when we control for alternative equity market information and for accounting drivers of risk. Thus, monitoring changes in CDS market prices could assist regulators and supervisors in forecasting future distress in individual banks, thus providing indirect market discipline.

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Table 1: **Sample Selection and Summary Statistics**

Panel A shows the number of banks and failures for every year of our sample period. We also include a geographical breakout which lists the number of firms, whose headquarters are based in Europe (EU) or the United States of America (US). Failure rate is the number of failures divided by the number of firms. This table also shows the summary statistics for the following variables during the period 2005-2011 for both the whole sample (Panel B) and the sample of failed banks (Panel C): the annual log change in the CDS spread (ΔCDS), the difference between the log change in the CDS spread and the log change in the CDX index spread (for US financial firms) or the iTraxx index spread for European financial firms ($\Delta EXCDS$), the idiosyncratic component of the log change in the CDS spread ($\Delta IDCDS$), the tier 1 regulatory capital ratio (T1RC), the ratio between the loan loss provisions and the book value of total assets (LLPTA), the ratio between the operating costs and the operating income (CI), the return on average equity (ROAE), the ratio between the liquid assets and the sum of the total deposits and short-term borrowing (LADEPST), the log of total assets (SIZE), the annual log stock return (STOCK), the distance-to-default measure (DD). CDS changes are expressed in basis points. All remaining variables are in percentages.

Panel A: Number of Firms and Failures per Year

Year	No. of firms (EU/US)	No. of failures (EU/US)	Failure rate (%) (EU/US)
2005	60 (49/11)	-	-
2006	60 (49/11)	-	-
2007	60 (49/11)	-	-
2008	60 (49/11)	20 (11/9)	33.33 (22.45/81.82)
2009	40 (38/2)	7 (5/2)	17.50 (13.16/100)
2010	33 (33/0)	1 (1/0)	3.03 (3.03/0)
2011	32 (32/0)	2 (2/0)	6.25 (6.25/0)
2012	30 (30/0)	1 (1/0)	3.23 (3.23/0)

	Mean	Median	Std	Min	Max	Obs	Mean	Median	Std	Min	Max	Obs
	Panel B: Whole Sample						**Panel C: Failed Sample**					
ΔCDS	0.450	0.203	0.927	-2.070	2.944	278	0.531	-0.050	1.064	-1.708	2.944	101
$\Delta EXCDS$	0.239	0.111	0.579	-1.254	2.109	278	0.311	0.084	0.688	-1.254	2.109	101
$\Delta IDCDS$	0.247	0.008	0.734	-1.896	2.283	212	0.307	-0.099	0.876	-1.667	2.283	85
T1RC	9.438	8.595	2.717	5.130	18.100	286	8.136	7.965	1.492	5.130	12.900	82
LLPTA	0.297	0.234	0.269	-0.128	1.425	295	0.267	0.225	0.252	-0.018	1.425	90
CI	62.080	59.235	25.676	22.292	331.128	308	66.382	62.644	24.410	22.292	230.463	102
ROAE	11.068	12.270	9.111	-44.454	34.684	308	13.076	13.207	10.064	-26.763	32.176	103
LADEPST	25.078	21.473	16.520	0.979	75.422	308	29.814	26.113	18.734	3.549	69.049	103
SIZE	19.368	19.322	1.166	16.985	21.674	308	19.452	19.718	1.172	17.237	21.674	103
STOCK	1.419	7.835	35.609	-181.577	97.004	210	5.410	8.267	36.004	-181.577	63.750	81
DD	3.591	3.26	2.353	-1.090	14.370	208	3.476	3.040	2.275	-1.090	10.500	79

Table 2: **Logit Regressions of Failure Indicator on CDS Changes with Control Variables.**

*This table summarizes results of binary logit regressions of the failure indicator on CDS changes with control variables from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS is the log change in the CDS spread. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. STOCK is the log stock return. DD is the distance-to-default measure. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. We report 9 different specifications of the logit regressions (M1 to M9). For instance, M1 regresses the failure indicator on a constant and the log change in the CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
ΔCDS	1.59***	1.33***	1.35***	1.35***	1.35***	1.35***	1.33***	2.66***	3.35***
	(5.54)	(4.48)	(4.27)	(3.85)	(3.80)	(3.84)	(3.83)	(4.22)	(3.01)
$T1RC$		-0.30**	-0.30**	-0.43***	-0.43***	-0.46***	-0.46***	-0.81***	-1.07***
		(-2.33)	(-2.26)	(-2.71)	(-2.71)	(-2.79)	(-2.78)	(-2.81)	(-3.83)
$LLPTA$			84.34	112.66	101.32	126.02	123.59	349.97**	470.95***
			(0.82)	(1.07)	(0.90)	(1.04)	(1.02)	(2.15)	(2.80)
CI				0.02**	0.02	0.02	0.02	0.01	0.01
				(2.19)	(1.48)	(1.16)	(1.18)	(0.84)	(1.28)
$ROAE$					-0.01	-0.01	-0.01	-0.04	0.00
					(-0.23)	(-0.23)	(-0.28)	(-1.06)	(0.06)
$LADEPST$						0.02	0.01	0.06**	0.05*
						(0.62)	(0.45)	(2.08)	(1.71)
$SIZE$							0.08	0.03	0.08
							(0.31)	(0.10)	(0.23)
$STOCK$								-0.94	
								(-0.81)	
DD									-1.19**
									(-2.36)
$Constant$	-3.62***	-1.05	-1.35	-1.72	-1.54	-1.59	-2.94	-2.66	-1.34
	(-8.20)	(-0.97)	(-1.18)	(-1.24)	(-0.94)	(-0.91)	(-0.65)	(-0.43)	(-0.21)
$Pseudo\ R^2$	0.243	0.238	0.244	0.300	0.300	0.304	0.305	0.488	0.568
$Nobs$	278	249	249	249	249	249	249	175	175

Table 3: **ROC Curve Areas for Different Failure Models - Out of Sample Analysis**

This table reports the results of 1000 simulations for the area under the Receiver Operating Characteristics curve obtained using several logit models that calculate ex-ante bank default probabilities for year 2008. For each model, we estimate it during the 2005-2007 period using 50 banks randomly selected. We then use the estimated coefficients to predict default probabilities of the remaining 10 banks in our sample. The models are based on the following three sets of variables (and their combinations) used as covariates to predict failure: accounting metrics, stock market variables (STOCK and DD) and ΔCDS*. The accounting variables include the following: T1RC, LLPTA, CI, ROAE, LADEPST, SIZE. In column 2, we report the simulated mean area under the ROC curve (AUC) computed using the trapezoidal rule. Column 3 shows the simulated mean standard error for the AUC, column 4 reports the test statistic for the null hypothesis that the AUC is equal to 0.5, column 5 reports the simulated mean accuracy ratio (AR = 2 * (AUC - 0.5)). Finally, column 6 shows the t-statistic of a two-sample one-tailed t-test for the null hypothesis that there is equality between the simulated mean areas under the ROC curve obtained from a model using* ΔCDS *only and any of the other remaining models. All t-statistics are significant at the 1% level.*

Model	AUC	SE	z	AR	t-test
ΔCDS	0.64	0.0913	6.98	0.27	-
$STOCK$	0.49	0.1023	4.78	-0.02	68.94
$Accounting$	0.53	0.0990	5.33	0.06	39.70
DD	0.78	0.0847	9.41	0.55	-41.54
$\Delta CDS + STOCK$	0.60	0.1072	5.59	0.20	14.49
$\Delta CDS + DD$	0.70	0.0975	7.38	0.40	-15.34
$\Delta CDS + Accounting$	0.53	0.1058	5.03	0.06	36.24
$STOCK + Accounting$	0.52	0.1178	4.44	0.05	361.90
$DD + Accounting$	0.58	0.1172	4.98	0.16	16.11
$\Delta CDS + STOCK + Accounting$	0.52	0.1259	4.14	0.04	35.45
$\Delta CDS + Accounting + DD$	0.54	0.1258	4.28	0.08	30.16

Online Appendix to

“Credit Default Swaps as Indicators of Bank Financial Distress”

by Davide Avino, Thomas Conlon and John Cotter

A. Definitions of Variables and Motivating Literature

Variables	Mnemonics	Expected Sign	Source
Dependent variables - Binary			
Failure indicator			
Downgrade indicator			
Dependent variables - Continuous			
ROAA volatility			
Z-score			
Financial accounting variables			
Capital adequacy			
Tier 1 regulatory capital ratio	*T1RC*	-	Demirguc-Kunt *et al.* (2013); Beltratti and Stulz (2012)
Asset quality			
Loan loss provisions to total assets	*LLPTA*	+	Poghosyan and Čihak (2011); Curry *et al.* (2008)
Management quality			
Cost to income ratio	*CI*	+	Cole and White (2012); Mannasoo and Mayes (2009)
Earnings quality			
Return on average equity	*ROAE*	-	Poghosyan and Čihak (2011); Arena (2008)
Liquidity			
Liquid assets to total deposits and borrowing	*LADEPST*	-	Beltratti and Stulz (2012)
Size of institution			
Natural logarithm of total assets	*SIZE*	-	Molyneux *et al.* (2014); Curry *et al.* (2008).
Financial market variables			
CDS market			
Yearly log change in senior CDS spread	ΔCDS	+	
Yearly log change in senior excess CDS spread	$\Delta EXCDS$	+	
Yearly log change in senior idiosyncratic CDS spread	$\Delta IDCDS$	+	
Log of senior CDS spread	*CDS*	+	
Volatility of daily log changes in senior CDS spread over the past 3 months	*CDSVOL*	+	
Yearly log change in subordinated CDS spread	ΔCDS_{SUB}	+	
3-month log change in senior CDS spread	$\Delta CDS3M$	+	
6-month log change in senior CDS spread	$\Delta CDS6M$	+	
9-month log change in senior CDS spread	$\Delta CDS9M$	+	
Equity market			
Yearly log stock return	*STOCK*	-	Distinguin *et al.* (2006)
Distance-to-Default	*DD*	-	Gropp *et al.* (2006)

Table A.1: **Logit Regressions of Failure Indicator on CDS Changes of 3, 6, 9 and 12 Months**

This table summarizes results of binary logit regressions of the failure indicator on CDS log changes of the past 3, 6, 9 and 12 months before the portfolio formation (end of each year) from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. $\Delta CDS3M$ *is the 3-month log change in the CDS spread.* $\Delta CDS6M$ *is the 6-month log change in the CDS spread.* $\Delta CDS3M$ *is the 9-month log change in the CDS spread.* ΔCDS *is the annual log change in the CDS spread. STOCK is the annual log stock return.* $Pseudo\ R^2$ *is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. We report 6 different specifications of the logit regressions (M1 to M6). For instance, M1 regresses the failure indicator on a constant and the 3-month log change in the CDS spread.*

	M1	M2	M3	M4	M5	M6
$\Delta CDS3M$	2.65*** (3.22)					
$\Delta CDS6M$		1.49*** (5.41)				
$\Delta CDS9M$			1.38*** (5.25)			
ΔCDS				1.59*** (5.54)		2.09*** (5.77)
$STOCK$					-0.56 (-1.13)	-1.94** (-2.24)
Constant	-2.59*** (-8.62)	-2.99*** (-9.43)	-3.03*** (-8.83)	-3.62*** (-8.20)	-2.15*** (-9.51)	-4.41*** (-7.00)
$Pseudo\ R^2$	0.136	0.186	0.185	0.243	0.006	0.312
Nobs	280	271	268	278	210	193

Table A.2: **Logit Regressions of Failure Indicator on CDS Changes with Control Variables During the Period 2005-2008**

*This table summarizes results of binary logit regressions of the failure indicator on CDS changes from 2005 to 2008. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS is the log change in the CDS spread. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. STOCK is the log stock return. DD is the distance-to-default measure. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. We report 9 different specifications of the logit regressions (M1 to M9). For instance, M1 regresses the failure indicator on a constant and the log change in the CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
ΔCDS	2.17***	2.30***	2.44***	2.37***	2.39***	2.47***	2.28***	3.25*	3.90**
	(5.25)	(3.53)	(3.67)	(3.62)	(3.51)	(3.84)	(4.10)	(1.95)	(2.01)
$T1RC$		-0.33*	-0.37*	-0.43*	-0.45*	-0.49*	-0.49*	-0.48	-2.93
		(-1.93)	(-1.93)	(-1.95)	(-1.80)	(-1.95)	(-1.74)	(-1.46)	(-1.54)
$LLPTA$			-123.75	-122.09	-117.10	-100.48	-159.55	17.14	1125.49
			(-0.62)	(-0.58)	(-0.57)	(-0.48)	(-0.84)	(0.07)	(1.18)
CI				0.02	0.03	0.02	0.02	-0.00	-0.20
				(1.22)	(1.09)	(0.90)	(0.52)	(-0.07)	(-1.19)
$ROAE$					0.01	0.02	0.01	-0.03	-0.03
					(0.27)	(0.34)	(0.12)	(-0.31)	(-0.16)
$LADEPST$						0.02	-0.02	0.00	0.14
						(0.46)	(-0.41)	(0.02)	(1.20)
$SIZE$							0.76**	1.07**	2.95*
							(1.99)	(2.47)	(1.87)
$STOCK$								2.00	
								(0.37)	
DD									-7.38
									(-1.43)
$Constant$	-4.56***	-2.64*	-2.25	-3.09	-3.45	-3.51	-16.55**	-24.25***	-22.60*
	(-6.31)	(-1.67)	(-1.30)	(-1.62)	(-1.53)	(-1.55)	(-2.36)	(-3.10)	(-1.96)
$Pseudo\ R^2$	0.414	0.416	0.423	0.433	0.433	0.436	0.477	0.557	0.718
$Nobs$	150	126	126	126	126	126	126	97	97

Table A.3: **Logit Regressions of Failure Indicator on CDS Spread Changes for Different Categories of Banks**

*This table summarizes results of binary logit regressions of the failure indicator on CDS spread changes of banks with different specializations and listing status. The sample period is from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS is the log change in the CDS spread. COOP is a dummy variable which equals 1 for cooperative banks and zero otherwise; INVB is a dummy variable which equals 1 for investment banks and zero otherwise; LISTED is a dummy variable which equals 1 for listed banks and zero otherwise. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively.*

	M1	M2	M3
ΔCDS	1.36***	1.12***	1.31**
	(3.88)	(2.86)	(2.43)
$COOP \times \Delta CDS$	-0.53		
	(-0.73)		
$INVB \times \Delta CDS$		1.35**	
		(2.59)	
$LISTED \times \Delta CDS$			0.03
			(0.06)
$T1RC$	-0.47***	-0.48***	-0.46***
	(-2.82)	(-2.69)	(-2.77)
$LLPTA$	120.21	144.71	122.90
	(0.98)	(1.10)	(1.01)
CI	0.02	0.02	0.02
	(1.17)	(1.12)	(1.18)
$ROAE$	-0.01	0.00	-0.01
	(-0.33)	(0.12)	(-0.28)
$LADEPST$	0.01	-0.00	0.01
	(0.43)	(-0.10)	(0.45)
$SIZE$	0.04	-0.11	0.08
	(0.15)	(-0.40)	(0.31)
$Constant$	-2.04	0.76	-2.95
	(-0.45)	(0.17)	(-0.65)
$Pseudo\ R^2$	0.309	0.344	0.305
$Nobs$	249	249	249

Table A.4: **Logit Regressions of Failure Indicator on Alternative CDS Metrics**

*This table summarizes results of binary logit regressions of the failure indicator on alternative CDS metrics from 2005 to 2012, using a variety of CDS derived metrics. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS is the log change in the CDS metric. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. $STOCK$ is the log stock return. DD is the distance-to-default measure. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. 5 sets of regressions are reported, as follows: in M1 and M2 ΔCDS corresponds to $\Delta EXCDS$, which is the difference between the 12-month log change in the CDS spread and the 12-month log change in the CDX index spread (for US financial firms) or the iTraxx index spread (for European financial firms). In M3 and M4, ΔCDS is the idiosyncratic component of the log change in the CDS spread, after controlling for market factors ($\Delta IDCDS$). In order to calculate the idiosyncratic component, we first regress daily CDS spread changes on a constant and either CDX index changes (for US firms) or iTraxx index changes (for European firms). The idiosyncratic CDS change, for each bank, is the residual from the market model on the last day of each year (expressed on an annual basis). CDX and iTraxx index spreads are obtained from Bloomberg. M5 and M6 treat ΔCDS as the log change of the 5^{th} percentile of the daily CDS spread , M7 and M8 take ΔCDS as the log change of the 95^{th} percentile of the daily CDS spread and in M9 and M10 ΔCDS is the log change of the average daily CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
ΔCDS	2.04***	2.83***	2.24***	2.95***	0.17	-1.36**	2.81***	5.66***	1.85***	3.58***
	(3.86)	(3.09)	(4.60)	(3.63)	(-0.47)	(-2.47)	(4.47)	(2.84)	(4.52)	(3.25)
$T1RC$	-1.05***	-1.30***	-0.95***	-1.23***	-0.84***	-1.10***	-1.00***	-1.45***	-0.90***	-0.96***
	(-3.06)	(-4.19)	(-3.03)	(-3.55)	(-3.71)	(-3.99)	(-3.58)	(-3.51)	(-3.85)	(-4.32)
$LLPTA$	343.82**	463.30***	217.26	427.75**	273.77*	416.17***	447.35***	641.21**	271.37*	224.44
	(1.98)	(3.11)	(1.11)	(2.48)	(1.73)	(2.90)	(2.89)	(2.57)	(1.65)	(1.43)
CI	0.02**	0.02**	0.02*	0.01	0.01	0.02**	0.01	0.01	0.01	0.01
	(2.34)	(2.31)	(1.81)	(0.64)	(1.31)	(2.26)	(1.24)	(0.92)	(1.02)	(1.02)
$ROAE$	-0.04	0.04	-0.00	0.04	-0.04	0.03	-0.05	-0.01	-0.04	0.02
	(-1.30)	(1.22)	(-0.13)	(1.03)	(-0.86)	(0.75)	(-1.25)	(-0.49)	(-0.99)	(0.50)
$LADEPST$	0.05	0.03	0.03	0.08	0.05	0.03	0.09**	0.12**	0.07**	0.05*
	(1.42)	(0.94)	(0.61)	(1.17)	(1.36)	(0.86)	(2.46)	(2.55)	(2.01)	(1.82)
$SIZE$	0.22	0.32	0.35	0.07	0.25	0.34	-0.01	0.03	0.18	0.28
	(0.76)	(0.92)	(0.89)	(0.13)	(0.75)	(1.04)	(-0.04)	(0.09)	(0.56)	(0.94)
$STOCK$	0.32		-1.74		0.92		0.96		1.96*	
	(0.41)		(-1.42)		(0.95)		(0.90)		(1.80)	
DD		-1.71***		-2.00***		-1.42***		-1.32***		-0.79***
		(-3.04)		(-4.73)		(-3.93)		(-3.05)		(-2.84)
$Constant$	-2.74	-0.89	-5.95	3.50	-3.28	-0.36	-1.01	-1.45	-2.83	-1.36
	(-0.50)	(-0.13)	(-0.76)	(-0.30)	(-0.58)	(-0.06)	(-0.16)	(-0.20)	(-0.48)	(-0.25)
$Pseudo\ R^2$	0.385	0.562	0.456	0.613	0.242	0.468	0.472	0.577	0.358	0.402
$Nobs$	175	175	139	139	175	175	175	175	175	175

Table A.5: **OLS Regressions of ROAA Volatility and Z-score and Logit Regressions of Downgrade Indicator on CDS Changes**

*This table summarizes results of OLS regressions of ROAA volatility on CDS Changes (M1, M2 and M3), OLS regressions of Z-score on CDS Changes (M4, M5 and M6) and binary logit regressions of downgrade indicator on CDS Changes (M7, M8, and M9). The sample period is from 2005 to 2012. The ROAA volatility is the standard deviation of the ROAA for each firm over the subsequent 12 months. The Z-score refers to the 12 months following portfolio formation. The downgrade indicator is 1 (0) if the firm is first downgraded (not downgraded) by any of the major rating agencies (Fitch, Moody's or Standard & Poor's) during the subsequent 12 months.ΔCDS is the log change in the CDS spread. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. STOCK is the log stock return. DD is the distance-to-default measure. R^2 is the value of the adjusted (McFadden) R-squared for OLS regressions (logit regressions). Nobs is the number of observations. In parentheses, we report the t-statistics for OLS regressions and z-statistics (adjusting standard errors using the Huber-White method) for logit regressions. *, ** and *** denote significance at the 10%, 5% and 1%, respectively.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
ΔCDS	0.10	0.08***	0.09***	-18.45***	-24.27***	-21.74***	0.88***	1.15***	0.45
	(1.52)	(4.27)	(4.22)	(-4.78)	(-4.26)	(-3.42)	(4.64)	(3.80)	(1.26)
$T1RC$		-0.00	-0.00		0.93	1.36		-0.06	-0.05
		(-0.56)	(-0.42)		(0.39)	(0.56)		(-0.39)	(-0.42)
$LLPTA$		23.29***	20.46***		-2771.12	-2554.60		200.20	360.68**
		(2.86)	(2.64)		(-1.19)	(-1.16)		(1.27)	(2.00)
CI		0.00	0.00		-0.21	-0.20		0.02	0.03
		(1.09)	(0.96)		(-0.87)	(-0.85)		(1.07)	(1.07)
$ROAE$		-0.00	-0.00		0.02	-0.22		0.07	0.05
		(-1.51)	(-1.36)		(0.03)	(-0.31)		(1.49)	(1.36)
$LADEPST$		0.00**	0.00**		-0.98**	-1.00**		0.02	0.03
		(2.15)	(2.05)		(-2.37)	(-2.43)		(1.21)	(1.38)
$SIZE$		0.00	0.00		8.36*	8.32*		0.35	0.26
		(0.03)	(0.12)		(1.79)	(1.79)		(1.41)	(1.00)
$STOCK$		0.06			-3.41			-4.57**	
		(1.16)			(-0.21)			(-2.50)	
DD			0.00			2.39			-0.51***
			(0.48)			(0.91)			(-2.83)
$Constant$	0.38***	0.10	0.06	58.06***	-60.35	-71.23	-1.49***	-11.76**	-8.50
	(5.72)	(0.33)	(0.18)	(15.65)	(-0.69)	(-0.81)	(-6.80)	(-2.35)	(-1.57)
R^2	0.004	0.198	0.193	0.057	0.116	0.119	0.114	0.300	0.304
$Nobs$	366	175	175	361	174	174	188	118	118

Table A.6: **Logit Regressions of Failure Indicator on Subordinated CDS Changes**

*This table summarizes results of binary logit regressions of the failure indicator on subordinated CDS changes from 2005 to 2012 for the firms for which subordinated CDS are also available. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS_{SUB} is the log change in the subordinated CDS spread. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. STOCK is the log stock return. DD is the distance-to-default measure. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. We report 9 different specifications of the logit regressions (M1 to M9). For instance, M1 regresses the failure indicator on a constant and the log change in the subordinated CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
ΔCDS_{SUB}	1.17***	1.01***	1.03***	1.07***	1.08***	1.08***	1.07***	1.42***	0.97*
	(3.34)	(3.08)	(3.14)	(2.93)	(2.91)	(2.92)	(2.84)	(3.84)	(1.74)
$T1RC$		-0.35**	-0.35**	-0.51***	-0.52***	-0.52***	-0.56**	-0.74***	-0.86***
		(-2.19)	(-2.10)	(-2.77)	(-2.74)	(-2.66)	(-2.34)	(-2.88)	(-3.49)
$LLPTA$			94.60	119.67	146.13	147.17	145.76	166.84	187.79
			(0.70)	(0.83)	(0.98)	(0.92)	(1.12)	(0.81)	(1.00)
CI				0.02**	0.02**	0.02*	0.02**	0.00	-0.01
				(2.36)	(2.13)	(1.91)	(2.34)	(0.15)	(-0.78)
$ROAE$					0.02	0.02	0.01	-0.02	0.00
					(0.48)	(0.45)	(0.40)	(-0.50)	(0.07)
$LADEPST$						0.00	-0.01	0.05	0.10**
						(0.02)	(-0.35)	(1.22)	(2.13)
$SIZE$							0.23	0.09	-0.49
							(0.66)	(0.23)	(-1.05)
$STOCK$								-1.22	
								(-0.97)	
DD									-1.24***
									(-3.92)
$Constant$	-3.37***	-0.28	-0.61	-0.85	-1.19	-1.19	-5.17	-1.31	13.32
	(-6.65)	(-0.22)	(-0.45)	(-0.62)	(-0.79)	(-0.80)	(-0.81)	(-0.19)	(1.53)
$Pseudo\ R^2$	0.147	0.188	0.196	0.252	0.255	0.255	0.259	0.342	0.455
$Nobs$	175	165	165	165	165	165	165	127	127